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Railway Rolling Stock Fleet Predictive Maintenance Data Analytics

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Abstract

In this paper predictive maintenance data analytics model is presented within the framework of stochastics point process. The concept of predictive maintenance is supported by data analytics model algorithms development. The generalised proportional intensity model (GPIM) is proposed. The model employs analytics, methods and techniques that use asset data, such as condition and loading data or experience, to detect or predict changes in the physical condition of equipment. Condition monitoring of train doors as a critical system is considered. The data arising from monitoring the state of the door systems occur randomly. Numerical example presented of modelling process considers the way in which intermittent failure data of the door is censored by preventive maintenance. Simulation of the GPIM model is used to predict the time to failure of the door system in terms of the expected cost per unit time. The cost model is inspired by a study of the practices in the railway industry. The use of the GPIM in this paper contributes to a wider shift towards integrating predictive maintenance and service operations in the railway industry.

Keywords: predictive maintenance, condition monitoring, rolling stock, stochastic process, data analytics.

1 Introduction

The fourth industrial revolution continues to integrate the digital, physical asset and human intervention. Data analytics is changing the way railway assets are designed, developed and manufactured. There is growing pressure in the railway industry to improve rolling stock fleet safety, performance, availability and reliability due to a variety of reasons such as unplanned downtime, delays and cancellation of services, customer satisfaction, and negative media publicity on fleet service operations. Determining the optimal time for maintenance enables faults to be identified and

eliminated with the necessary maintenance interventions. The rolling stock train operating companies in the United Kingdom are increasing their capacity by acquiring new fleets in addition to existing fleets. The implementation of condition based maintenance technologies is important to optimise train fleet availability and reliability. The challenges of the significant number of maintenance, condition monitoring and remote monitoring data information from different systems require adequate maintenance management, planning and scheduling in order to ensure high availability and reliability and reduced downtimes.

1.1 Predictive Maintenance

The application of predictive maintenance data analytics to predict the future failures in train fleet and prescribing the most effective preventive maintenance measure is growing in potential and is yet to reach its maturity stage in the railway industry. Predictive maintenance has a lot of potential to ensure that a certain level of service reliability and availability is achieved. Predictive maintenance implies the constant monitoring of a piece of equipment through the measuring of all relevant variables. The concept of predictive maintenance is supported by data analytics and model algorithms development; autonomous operation of systems, self-coordination and self-diagnosis is allowed by access to both condition monitoring data, remote control and optimization algorithms. The advances in information technology make it less complicated to gather and analyse data [1] and these have thereby improved the ease-of-use of the analytics for predictive maintenance. The Usefulness of the data analytics on the other hand has improved by the emergence of smart algorithms and intelligent machines that can help to perform a predict-and-prevent practice instead of a fail-and-fix operation [2].

The use of computerised maintenance management system and reliable railway maintenance depend on the use of predictive maintenance and smart data analytics approaches. This involves harnessing and integrating the relevance of dynamic stochastic process methodology, and statistical analysis to detect the precursor of failure and anomalies to extend the lifetime of the train fleet systems. Stochastic processes are ways of quantifying the dynamic relationship of sequences of random events [3]. A stochastic model predicts a set of possible outcomes weighted by their likelihood and probabilities. The models play an important role in elucidating many areas of natural applications. Stochastic point processes have been applied to repairable systems. They are mathematical models characterized by highly localised events distributed randomly in a continuum. The continuum is time and the highly localised events are failures, which are assumed to occur at instants within the continuum [4]. The entire technique developed for point process models is potentially applicable to systems' failure data. In this paper the condition monitoring test trial data of the door is presented depicting signal pulse as intermittent failures is used and an attempt is made to predict the distribution of time to failure of train door components.

2 Technical data analysis

2.1 Condition monitoring

An extensive review of diagnostics and prognostics analysis implementing condition based maintenance models is discussed in [5]. Condition-based maintenance (CBM) can be used to monitor asset health regularly in order to maximize reliability and availability and also in determining necessary maintenance at the right time. A framework of condition based maintenance approach on rotating mechanical systems is discussed in [6]. A case study on the condition monitoring of railway equipment train rotary door operator is presented in [7]. Critical appraisal of other condition monitoring techniques and its application in the railway industry is discussed further in Section 2.

2.1.1 Door critical system

The Door Key Switch (DKS) and the Door Interlock Switch (DIS) contribute to technical incident resulting to delays in-service. The technical incidents in Table 1 below give an overview of top 3 failure modes.

Table 1. Top 3 Failure modes technical incidents

Year	Failure model 1	Failure mode 2	Failure mode 3
2012	DKS defective	DIS adjusted	DIS defective
2013	DKS defective	DIS adjusted	DIS defective
2014	DIS adjusted	DIS adjusted	DIS short circuit

PM is conducted to capture the top 3 failure modes every 7k miles in 2012 and 2013 and in 2014 PM is conducted at 10k miles. The percentage of incidents and delays caused by the top 3 failure modes is presented in Table 2

Table 2. Top 3 % technical incidents & delays

Year	Maintenance	% of incidents	% of delays
2012	7k miles	66%	75%
2013	7k miles	43%	35%
2014	10k miles	38%	16%

The percentage technical incidents and delays caused by the DIS and DKS top 3 failure modes decreases as the PM intervals are extended over the years to 10k miles.

2.1.2 Condition monitoring trial results

Condition monitoring trial is conducted fleet of train units. The trial incidents recorded show the most common causes of incidents attributed to the door DKS and DIS systems. The door slow to close is determined when the time taken to close the door is more than 8 seconds over the centre after pressing the door close button on the DKS Panel. Once the door close command is initiated the door release trigger and closes the Left Hand Side (LHS) or Right Hand Side (RHS). A “pulse” signal and the hustler alarm sound for 3 seconds before the doors start to close. It takes about 4 to 4.5 seconds for the door to close. For example if the door setting is calibrated with an additional 0.5 seconds it will flag many issues in relation to accuracy of timing.

Figure 1a indicates that the number of slow to close incidents on the door C is as high as 32 and this is due to the accuracy in the settings. However, after the rule refinement in the setting as shown in Figure 1b, it highlights that the number is reduced to 2 which in principle is a 93.75% decrease in false reports.

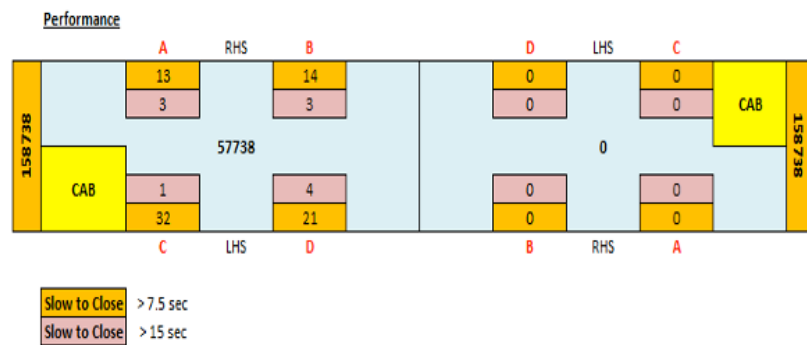


Figure 1a. Slow to close incidents

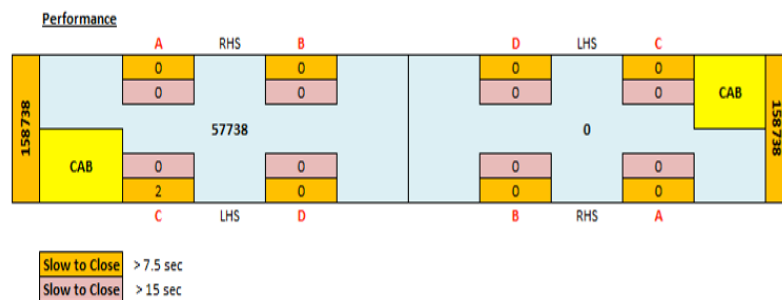


Figure 1b. Slow to close incidents

The condition monitoring trial on the doors has given us an insight and the capability to flag up potential failures as a form of a “signal pulse”. “Signal Pulse” monitors if the sensor signal from the DKS or DIS is active for less than a second (0ms – 1000ms). An example of the condition monitoring incidents recorded in Figure 2 below indicate intermittent electrical failure on DKS door C.

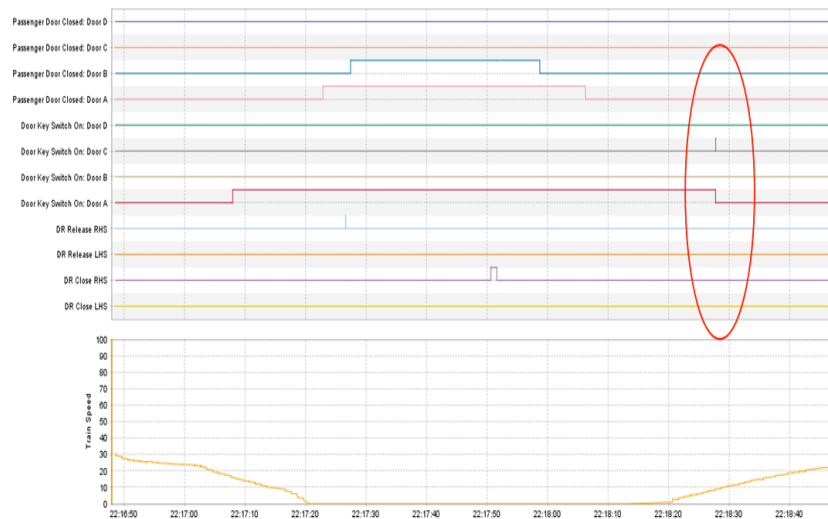


Figure 2: DKS door C signal pulse incident.

The door faults addresses root cause and hence identify potential failure modes. A comprehensive study using the reliability centred maintenance approach of the class train doors to identify critical classes of failure modes is presented in [8]. Reliability analysis of rolling stock failure patterns is discussed in [9]. From some of the literature consulted the preventive maintenance is considered to be one of the most difficult task to model in the field of maintenance and sometimes the result on preventive maintenance actions is somewhat cost effective but does not classify causes of breakdown incidents.

A failure mode, effects and criticality analysis of rolling stock critical systems is conducted in [10] and the outcome is used to further proposed a generic framework using risk-based maintenance. A delay time model is proposed in an attempt to model preventive maintenance policy of train doors presented in [11]. The difficulty of optimising the preventive maintenance of the doors is beneficial in economic terms however it is at an expense of reduced fleet availability for service operations. The design and evaluation of remote measurement for the online monitoring of railway vibration signals is discussed and analysis of vibrations results is presented in [12]. The paper provides a very good framework for utilizing on-line condition monitoring of railway assets. To this aim condition based maintenance is envisaged

as a way forward towards improving the maintenance actions and hence improve the reliability, and availability of rolling stock the door system.

3 Model simulation

3.1 Generalised proportional intensity model

Determining the optimal time for maintenance enables faults to be identified and eliminated with the necessary maintenance procedure. In this paper remote condition monitoring data samples coming off a train fleet that could lead to hidden failures is considered. Condition monitoring can be classified into two categories: completely observable systems and partially observable systems. For a completely observable system, the systems state can be completely observed or identified. A partially observable system is considered in this paper, and a data-driven predictive analytics for maintenance framework is presented in an attempt to construct a prognostics model to allow data visibility of the train fleet critical system, thus identifying faults early on. The technical feasibility of the use of the proposed model is used to identify the main precursors to potential failures. Stochastic models involving partial condition monitoring information are adopted. Under these circumstances it is important to allow for uncertainty. The stochastic model called the generalised proportional intensities model (GPIM) is proposed, with a baseline intensity function as a means of predicting the system failure on the train fleet. Algebraic expression of the GPIM in Eq(1) is given as;

$$\lambda(t) = \lambda_0(t) \left\{ \prod_{i=1}^{M(t)} r_i \right\} \left\{ \prod_{j=1}^{N(t)} s_j \right\} \exp(\mathbf{x}_t^T \boldsymbol{\gamma}) \quad (1)$$

Here $\lambda_0(t)$ is the baseline intensity function as for the GPIM described earlier, whilst r_i and s_j are the intensity scaling factors corresponding to preventive maintenance (PM) and corrective maintenance (CM) actions respectively. Furthermore, $M(t)$ and $N(t)$ are the total numbers of PM and CM actions in the time interval $(0, t]$, whilst \mathbf{x}_t is a vector of predictor variables at time t and $\boldsymbol{\gamma}$ is an unknown parameter vector of regression coefficients. The predictor variable could contain condition monitoring information that can cause a failure of the system.

3.2 GPIM Simulation

PM of 10k miles horizon interval is chosen in GPIM model and expected mean cost per unit time over k simulation runs (1000 times) using the cost model given below

in equation Eq(2) and the estimated expected number of failures in the interval $v(t)$ is the average of v_i .

$$c(t) = \frac{\sum_{i=1}^k (c_{PM}^i + v_i c_{CM}^i)}{kt} \quad (2)$$

The log-linear baseline intensity and constant scaling (LCC) is used for the model simulation and compared with LCC with covariate of predictor variable represented as DT. The estimated cost curve is given in Figure 3 below.

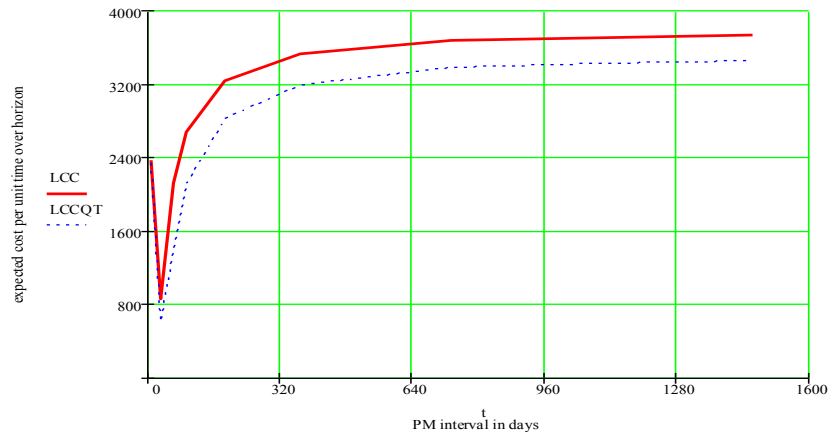


Figure 2. Simulated cost curve for the door

3.3 Results

The forecasts of the expected cost over the fixed ten years horizon for the models is presented. For the LCC with constant CM scaling and LCCQT with predictor variable, there appear to be minimum expected costs at a regular interval of 30 days (four weeks) with 858.53 and 607.0 units respectively. The primary goal of for the adoption of predictive maintenance model using remote condition monitoring data information and fitting the GPIM to the data is to help enhance reliability improvement, higher customer satisfaction, cost reduction, and life extension and aging systems, as well as environmental risk. The study and results presented highlight critical system PM times that can allow engineers to identify maintenance improvement, plan routine maintenance and overhaul specifications to achieve higher operational safety, performance and reliability.

The application of the GPIM model to the a variety of condition monitoring data information is still on-going at the moment and this new knowledge is expected to enhance maintenance effectiveness and reduce the amount of technical in-service failures. The model result presented in this paper helps to:

- Select the most appropriate technique for the component/system maintenance
- Deal with each type of failure process including hidden and linked failures
- Maximise usable life of the asset
- Choose the most cost-effective and enduring maintenance approach

The main contribution of this paper is to demonstrate the relevance of the application of the generalised proportional intensities model to condition monitoring data and historical data information. The implementation of the new knowledge to safety critical system on train fleet in order to give the maintenance engineers the ability to transform raw data to valuable information to support cost effective decision making on predictive maintenance.

4. Conclusion

The generalised proportional intensities model (GPIM) using the stochastics process framework. The condition monitoring data information is considered in the modelling and simulation. This paper also give series of example scenarios associated with the rolling stock door system. The challenges associated to door performance and reliability improvement, and the effect it has on service operations are clearly highlighted. The condition monitoring trial result conducted on the door systems is presented. The outcome of the trial demonstrates a new development towards monitoring state of the critical components (DKS and DIS) of the door systems is addressed. The data arising from monitoring of the door system incident occur randomly and stochastic point processes. The model considers the way in which intermittent failure data is censored by preventive maintenance. The model is inspired by the study of the practices in the railway industry. Simulation of the GPIM model to predict the time to failure of the door system and the expected cost per unit time.

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